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(54) **SELF-SUPERVISED LEARNING FOR ANOMALY DETECTION AND LOCALIZATION**

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G06N 3/08	(2023.01)
G06V 10/22	(2022.01)
G06V 10/774	(2022.01)
G06V 10/82	(2022.01)

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CPC ***G06F 18/2155*** (2023.01); ***G06N 3/08*** (2013.01); ***G06V 10/22*** (2022.01)

(58) **Field of Classification Search**
CPC G06F 18/2155; G06N 3/08; G06V 10/22; G06V 10/774; G06V 10/82; G06T 2207/20132
See application file for complete search history.

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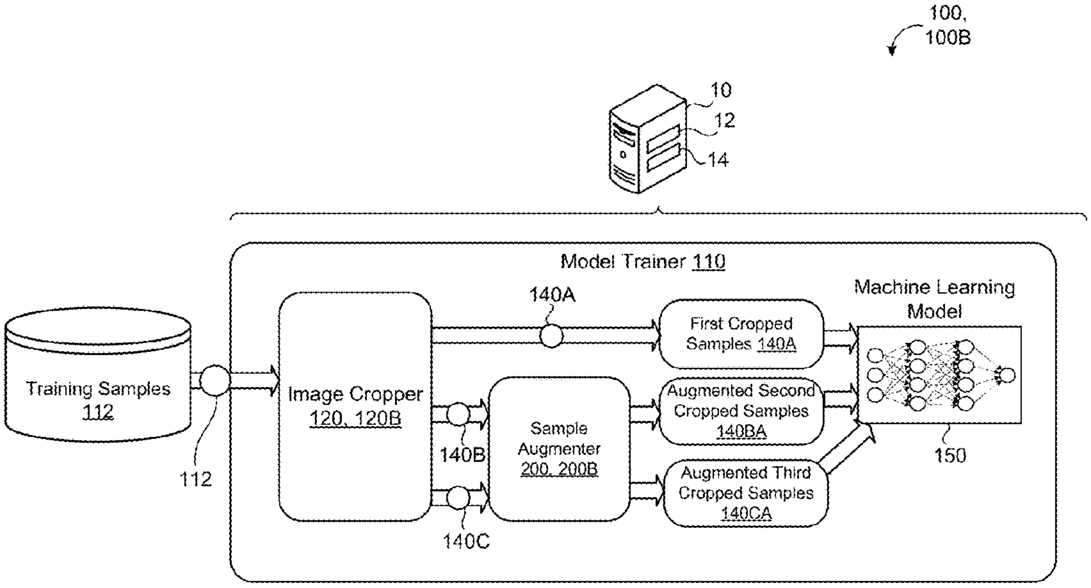
(57) **ABSTRACT**

A method for training a machine learning model includes obtaining a set of training samples. For each training sample in the set of training samples, during each of one or more training iterations, the method includes cropping the training sample to generate a first cropped image, cropping the training sample to generate a second cropped image that is different than the first cropped image, and duplicating a first portion of the second cropped image. The method also includes overlaying the duplicated first portion of the second cropped image on a second portion of the second cropped image to form an augmented second cropped image. The first portion is different than the second portion. The method also includes training the machine learning model with the first cropped image and the augmented second cropped image.

20 Claims, 7 Drawing Sheets



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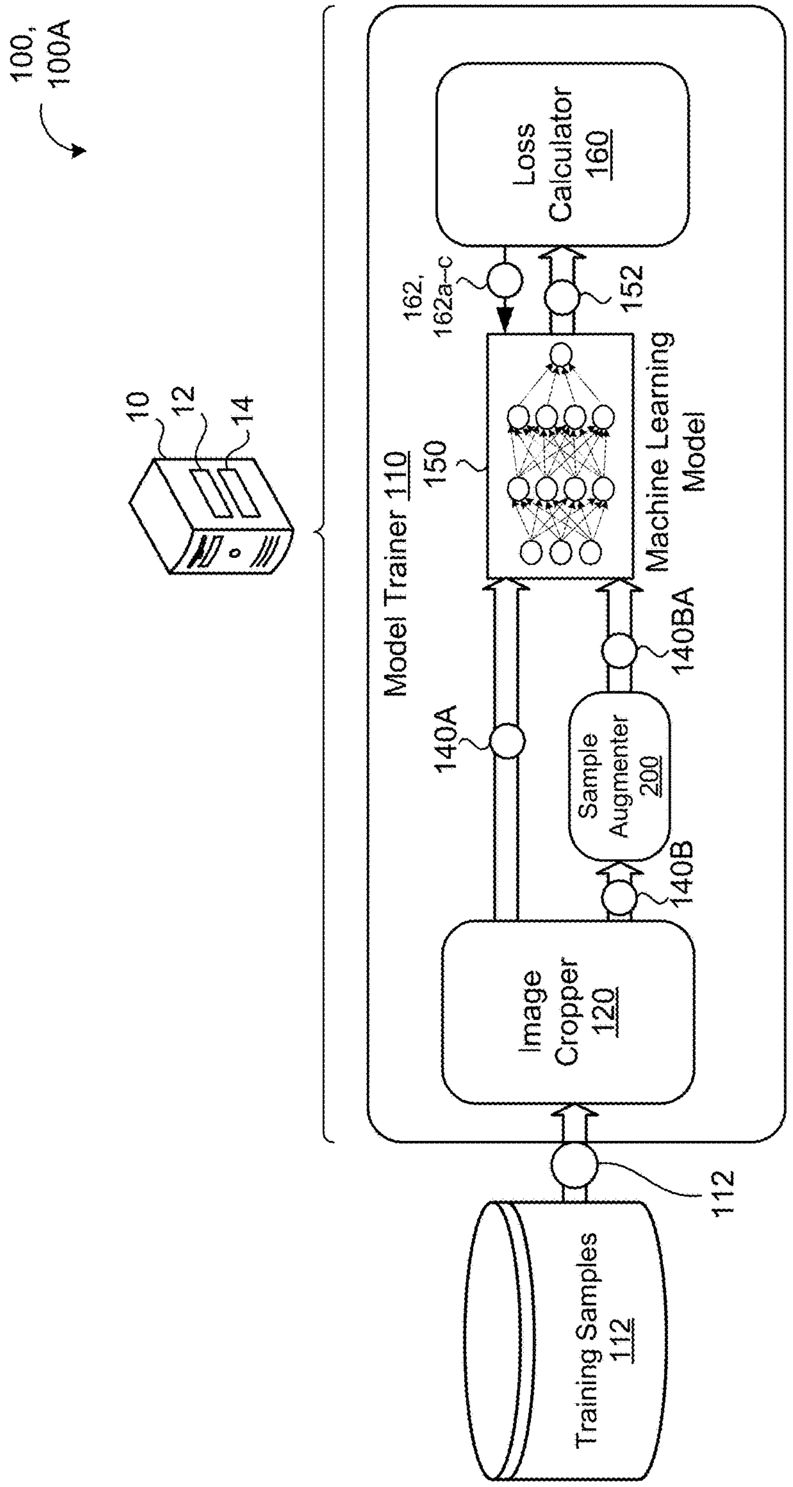
100,
100A
10
12
14
Model Trainer 110
Loss
Calculator
160
162,
162a–c
152
150
Machine Learning
Model
140A
140BA
Sample
Augmenter
200
140B
Image
Cropper
120
112
Training Samples
112

FIG. 1

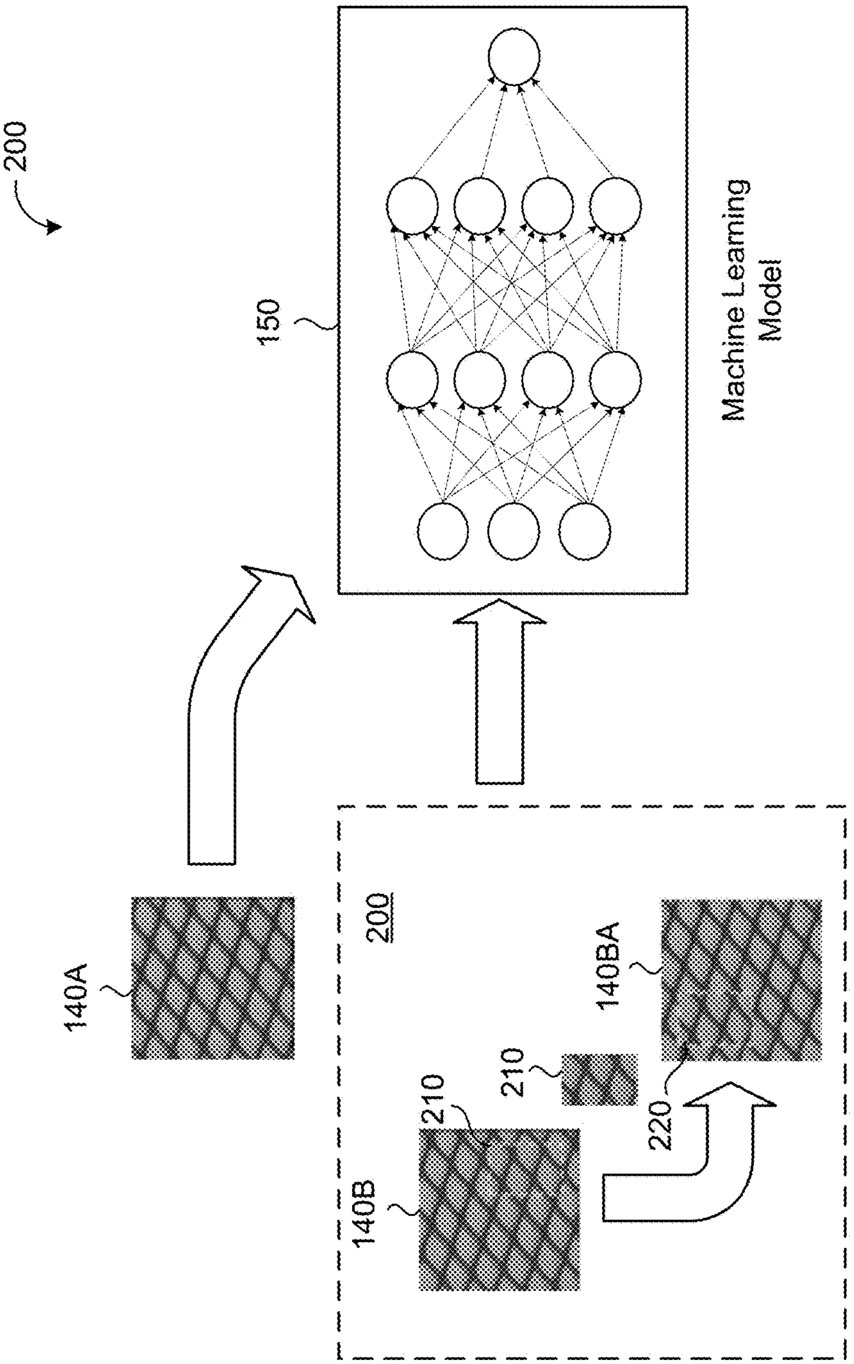
200
150
Machine Learning Model
140A
200
140BA
210
210
210
220
140B

FIG. 2

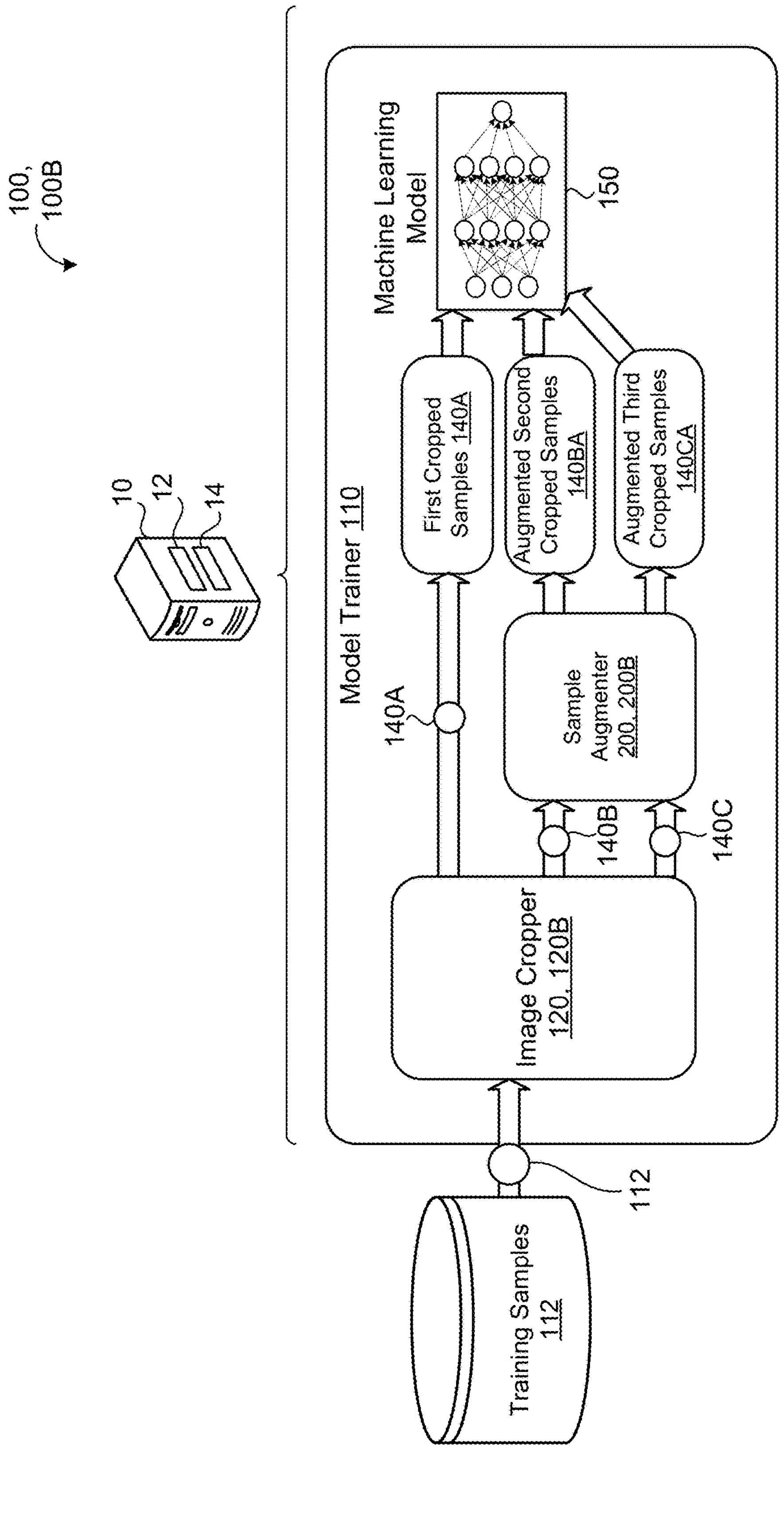
100, 100B
10
12
14
Model Trainer 110
Training Samples 112
112
Image Cropper 120, 120B
140A
140B
140C
Sample Augmenter 200, 200B
First Cropped Samples 140A
Augmented Second Cropped Samples 140BA
Augmented Third Cropped Samples 140CA
Machine Learning Model
150

FIG. 3

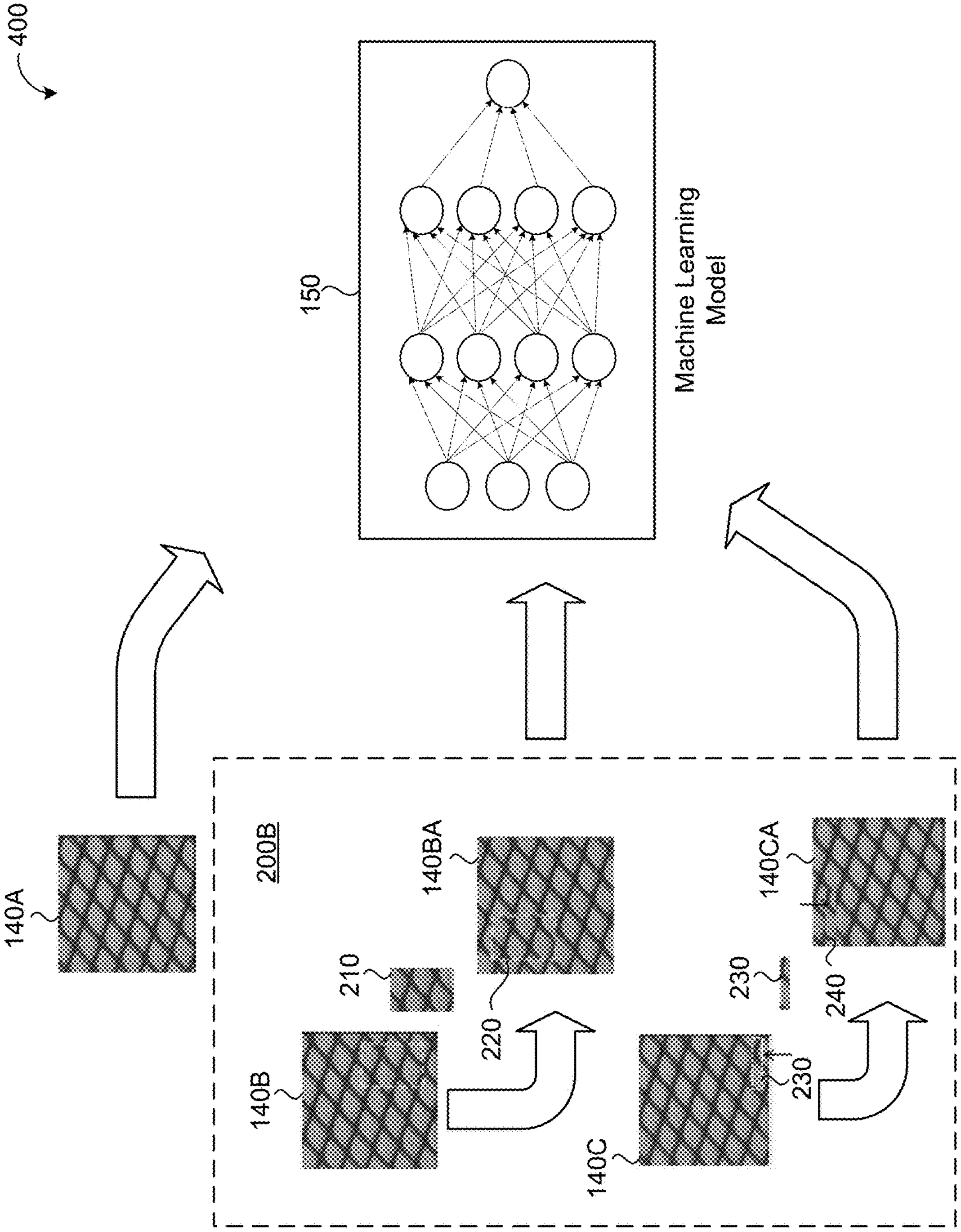
400
150
Machine Learning Model
140A
200B
140BA
210
140B
220
230
140CA
240
140C
230

FIG. 4

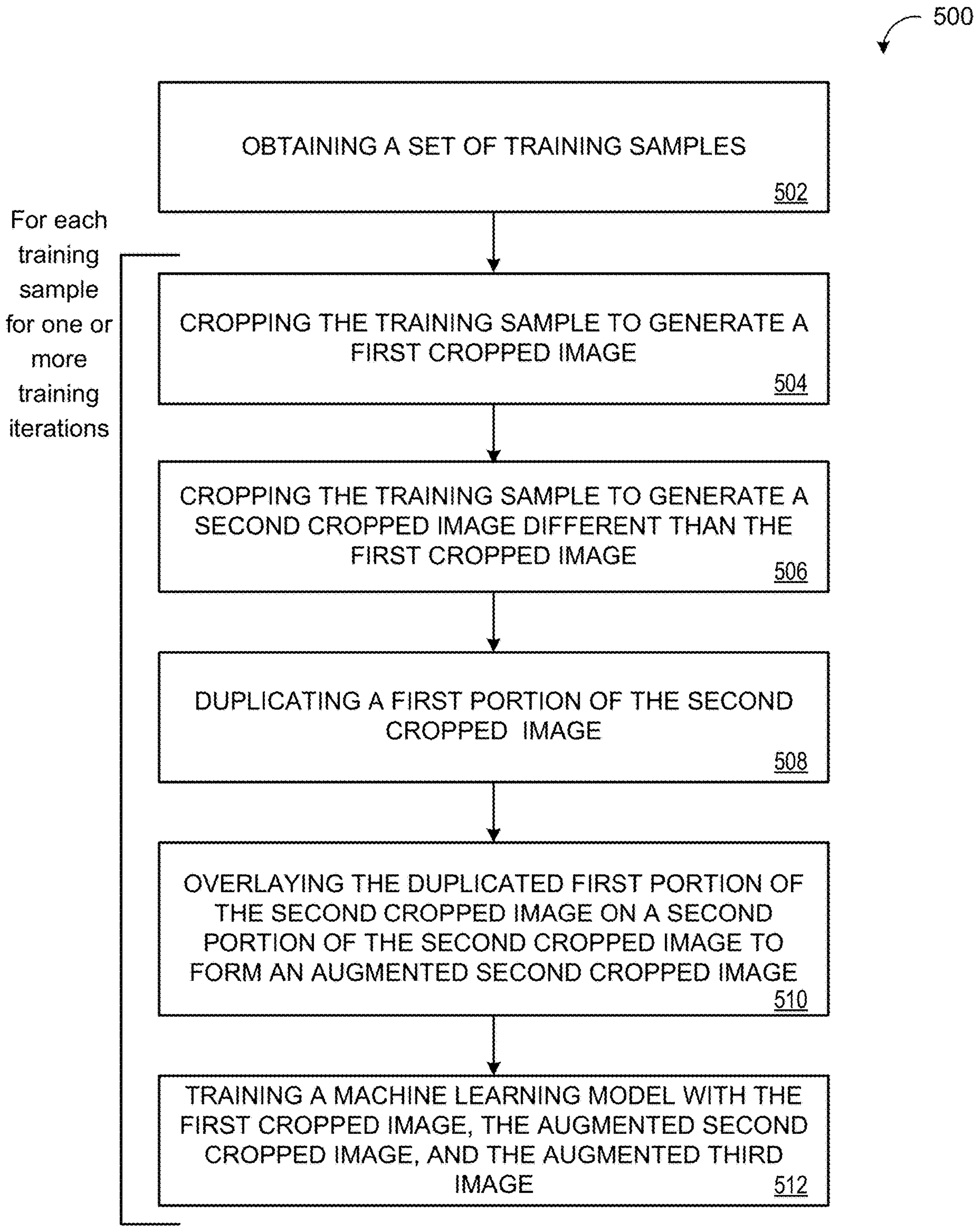
500
OBTAINING A SET OF TRAINING SAMPLES
502
For each training sample for one or more training iterations
CROPPING THE TRAINING SAMPLE TO GENERATE A FIRST CROPPED IMAGE
504
CROPPING THE TRAINING SAMPLE TO GENERATE A SECOND CROPPED IMAGE DIFFERENT THAN THE FIRST CROPPED IMAGE
506
DUPLICATING A FIRST PORTION OF THE SECOND CROPPED IMAGE
508
OVERLAYING THE DUPLICATED FIRST PORTION OF THE SECOND CROPPED IMAGE ON A SECOND PORTION OF THE SECOND CROPPED IMAGE TO FORM AN AUGMENTED SECOND CROPPED IMAGE
510
TRAINING A MACHINE LEARNING MODEL WITH THE FIRST CROPPED IMAGE, THE AUGMENTED SECOND CROPPED IMAGE, AND THE AUGMENTED THIRD IMAGE
512

FIG. 5

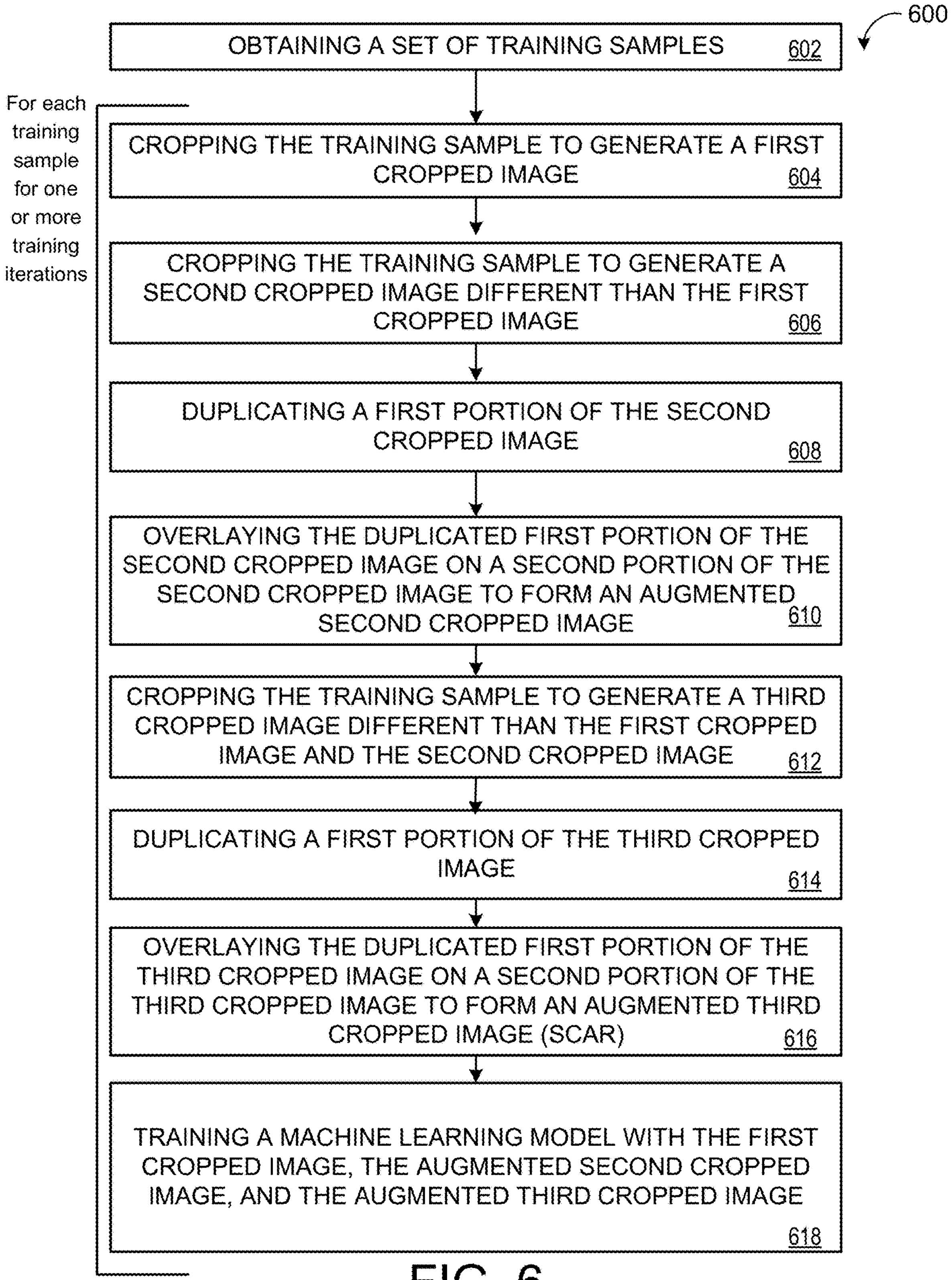
600
OBTAINING A SET OF TRAINING SAMPLES 602
For each training sample for one or more training iterations
CROPPING THE TRAINING SAMPLE TO GENERATE A FIRST CROPPED IMAGE 604
CROPPING THE TRAINING SAMPLE TO GENERATE A SECOND CROPPED IMAGE DIFFERENT THAN THE FIRST CROPPED IMAGE 606
DUPLICATING A FIRST PORTION OF THE SECOND CROPPED IMAGE 608
OVERLAYING THE DUPLICATED FIRST PORTION OF THE SECOND CROPPED IMAGE ON A SECOND PORTION OF THE SECOND CROPPED IMAGE TO FORM AN AUGMENTED SECOND CROPPED IMAGE 610
CROPPING THE TRAINING SAMPLE TO GENERATE A THIRD CROPPED IMAGE DIFFERENT THAN THE FIRST CROPPED IMAGE AND THE SECOND CROPPED IMAGE 612
DUPLICATING A FIRST PORTION OF THE THIRD CROPPED IMAGE 614
OVERLAYING THE DUPLICATED FIRST PORTION OF THE THIRD CROPPED IMAGE ON A SECOND PORTION OF THE THIRD CROPPED IMAGE TO FORM AN AUGMENTED THIRD CROPPED IMAGE (SCAR) 616
TRAINING A MACHINE LEARNING MODEL WITH THE FIRST CROPPED IMAGE, THE AUGMENTED SECOND CROPPED IMAGE, AND THE AUGMENTED THIRD CROPPED IMAGE 618

FIG. 6

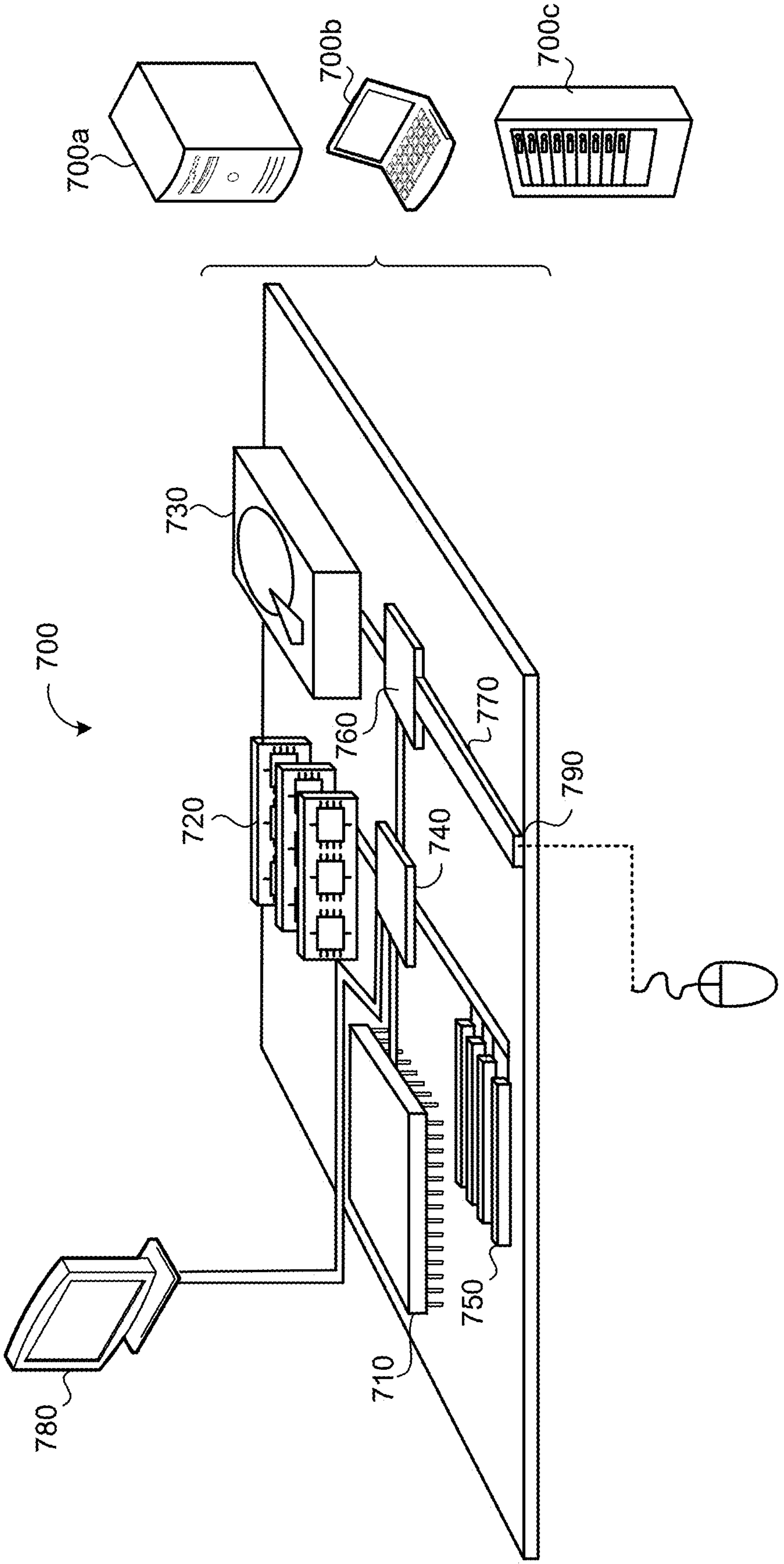

FIG. 7

SELF-SUPERVISED LEARNING FOR ANOMALY DETECTION AND LOCALIZATION

CROSS REFERENCE TO RELATED APPLICATIONS

This U.S. patent application claims priority under 35 U.S.C. § 119(e) to U.S. Provisional Application 63/113,780, filed on Nov. 13, 2020. The disclosure of this prior application is considered part of the disclosure of this application and is hereby incorporated by reference in its entirety.

TECHNICAL FIELD

This disclosure relates to self-supervised learning for anomaly detection and localization.

BACKGROUND

Anomaly detection using machine learning models aims at detecting an instance containing anomalous and defective patterns that are different from those seen in normal instances. Many problems from different application domains of computer vision exist for anomaly detection, including manufacturing defect detection, medical image analysis, and video surveillance. Unlike a typical supervised classification problem, anomaly detection problems face a few unique challenges. First, due to the nature of the problem, it is difficult to obtain a large amount of anomalous data, either labeled or unlabeled. Second, the differences between normal and anomalous patterns are often fine-grained as defective areas might be small and subtle in high-resolution images.

SUMMARY

One aspect of the disclosure provides a method for training a machine learning model. The method includes obtaining, at data processing hardware, a set of training samples. For each training sample in the set of training samples, during each of one or more training iterations, the method includes cropping, by the data processing hardware, the training sample to generate a first cropped image. The method also includes cropping, by the data processing hardware, the training sample to generate a second cropped image that is different than the first cropped image and duplicating, by the data processing hardware, a first portion of the second cropped image. The method also includes overlaying, by the data processing hardware, the duplicated first portion of the second cropped image on a second portion of the second cropped image to form an augmented second cropped image. The first portion is different than the second portion. The model also includes training, by the data processing hardware, the machine learning model with the first cropped image and the augmented second cropped image.

Implementations of the disclosure may include one or more of the following optional features. In some implementations, the duplicated first portion of the second cropped image has a rectangular shape with a variable length and width. In some implementations, overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image includes selecting a random location of the second cropped image for the second portion of the second cropped image and overlaying the duplicated first portion of the second cropped image at the selected random location.

In some examples, training the machine learning model with the first cropped image and the augmented second cropped image includes determining a first cross-entropy loss for the first cropped image, determining a second cross-entropy loss for the augmented second cropped image, and determining a total cross-entropy loss based on the first cross-entropy loss and the second cross-entropy loss. The total cross-entropy loss may include a sum of the first cross-entropy loss and the second cross-entropy loss.

Optionally, each training sample may be unlabeled. In some implementations, the machine learning model includes a convolutional neural network. In some implementations, the machine learning model is configured to detect anomalous patterns in image data. The method may further include, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, rotating, by the data processing hardware, the duplicated first portion of the second cropped image. In some implementations, the method further includes, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, applying, by the data processing hardware, a color jitter to the duplicated first portion of the second cropped image.

Another aspect of the disclosure provides a system for training a machine learning model. The system includes data processing hardware and memory hardware in communication with the data processing hardware. The memory hardware stores instructions that when executed on the data processing hardware cause the data processing hardware to perform operations. The operations include obtaining a set of training samples. For each training sample in the set of training samples, during each of one or more training iterations, the operations include cropping the training sample to generate a first cropped image and cropping the training sample to generate a second cropped image that is different than the first cropped image. The operations also include duplicating a first portion of the second cropped image and overlaying the duplicated first portion of the second cropped image on a second portion of the second cropped image to form an augmented second cropped image. The first portion is different than the second portion. The operations also include training the machine learning model with the first cropped image and the augmented second cropped image.

Implementations of the disclosure may include one or more of the following optional features. In some implementations, the duplicated first portion of the second cropped image has a rectangular shape with a variable length and width. In some examples, overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image includes selecting a random location of the second cropped image for the second portion of the second cropped image and overlaying the duplicated first portion of the second cropped image at the selected random location.

Optionally, training the machine learning model with the first cropped image and the augmented second cropped image may include determining a first cross-entropy loss for the first cropped image, determining a second cross-entropy loss for the augmented second cropped image, and determining a total cross-entropy loss based on the first cross-entropy loss and the second cross-entropy loss. The total cross-entropy loss may include a sum of the first cross-entropy loss and the second cross-entropy loss.

In some implementations, each training sample is unlabeled. In some implementations, the machine learning model includes a convolutional neural network. In some implementations, the machine learning model is configured to detect anomalous patterns in image data. The operations may further include, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, rotating, by the data processing hardware, the duplicated first portion of the second cropped image. In some implementations, the operations further include, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, applying, by the data processing hardware, a color jitter to the duplicated first portion of the second cropped image.

The details of one or more implementations of the disclosure are set forth in the accompanying drawings and the description below. Other aspects, features, and advantages will be apparent from the description and drawings, and from the claims.

DESCRIPTION OF DRAWINGS

FIG. **1** is a schematic view of a system for training a model for anomaly detection and localization.

FIG. **2** is a schematic view illustrating a learning method for anomaly detection and localization.

FIG. **3** is a schematic view of another system for training a model for anomaly detection and localization.

FIG. **4** is a schematic view illustrating a learning method for anomaly detection and localization using a scar technique.

FIG. **5** is a flowchart of an example arrangement of operations for a method of training a model for anomaly detection and localization.

FIG. **6** is a flowchart of an example arrangement of operations for a method of training a model for anomaly detection and localization using a scar technique.

FIG. **7** is a schematic view of an example computing device that may be used to implement the systems and methods described herein.

Like reference symbols in the various drawings indicate like elements.

DETAILED DESCRIPTION

Anomaly detection using machine learning models aims at detecting an instance containing anomalous and defective patterns that are different from those seen in normal instances. Many problems from different application domains of computer vision exist for anomaly detection, including manufacturing defect detection, medical image analysis, and video surveillance. Unlike a typical supervised classification problem, anomaly detection problems face a few unique challenges. First, due to the nature of the problem, it is difficult to obtain a large amount of anomalous data, either labeled or unlabeled. Second, the differences between normal and anomalous patterns are often fine-grained as defective areas might be small and subtle in high-resolution images.

Due to limited access to anomalous data, constructing an anomaly detector is often conducted under semi-supervised or one-class classification settings using normal data only (i.e., non-anomalous data). Because the distribution of anomaly patterns is generally unknown in advance, models are often trained to learn patters of normal instances and detect an anomaly when a test sample is not well represented

by these models. For example, an autoencoder that is trained to reconstruct normal data is used to declare anomalies when the data reconstruction error is high. Generative models declare a sample anomalous when a probability density is below a certain threshold. However, an anomaly score defined as an aggregation of pixel-wise reconstruction error or a negative probability density fails to capture high-level semantic information.

Implementations herein are directed toward a model trainer that provides robust training of a machine learning model configured for anomaly detection and localization. The model trainer uses a semi-supervised learning technique that does not require large quantities of anomalous data while still delivering accurate detection of fine-grained anomalous areas.

Referring to FIG. **1**, in some implementations, an example system **100**, **100**A includes a processing system **10**. The processing system **10** may be a single computer, multiple computers, or a distributed system (e.g., a cloud environment) having fixed or scalable/elastic computing resources **12** (e.g., data processing hardware) and/or storage resources **14** (e.g., memory hardware). The processing system **10** executes a model trainer **110**. The model trainer **110** trains a machine learning model **150** (e.g., a deep neural network (DNN)) to make predictions based on input data. For example, the model trainer **110** trains a convolutional neural network (CNN) of the machine learning model **150**. The model trainer **110** trains the machine learning model **150** on a set of training samples **112**. In some implementations, the set of the training samples **112** is stored at the storage resource **14**. Each of the training samples **112** may include an image or images of normal patterns (i.e., patterns that do not include anomalies). For example, the images of normal patterns have a resolution of 256×256 pixels. As will be described in more detail below, the model trainer **110** is configured to generate one or more augmented images with anomalies based on the image of normal patterns in accordance with some implementations. The one or more anomalous images generated by the model trainer **110** may be provided as augmentation input data to enhance or improve the training of the machine learning model **150**.

The model trainer **110** obtains the training samples **112**, in some implementations, from the storage resources **14** or other device suitable to store the training samples **112**. The training samples **112** may be unlabeled. In other words, one or more training samples (images) or each training sample in the set of the training samples **112** may not include a label indicting an anomaly, or lack thereof, in the corresponding training sample **112**.

In some implementations, the model trainer **110** includes an image cropper **120**. The image cropper **120** crops each image of the training samples **112** into a smaller size image (i.e., by removing a portion of the pixels of the original image). In some implementations, the image cropper **120** is configured to crop a 256×256 image (i.e., an image with 256 rows and 256 columns of pixels) into 64×64 image or 32×32 image. The image cropper **120** may crop a training sample **112** into one or more cropped images. For example, the image cropper may crop a respective training sample **112** into a first cropped image **140**A and a second cropped image **140**B. The first cropped image **140**A may be different than the second cropped image **140**B. For example, the image cropper **120** crops two different portions for the first cropped image **140**A and the second cropped image **140**B respectively. As discussed in more detail below, the portions of the image that the image cropper **120** selects to crop may be pseudo-random or random. The first and second cropped image **140**A, **140**B may be the same size or different sizes.

The model trainer **110**, in some implementations, includes a sample augmenter **200**. The sample augmenter **200** receives the second cropped image **140**B for each of the training samples **112** and generates an augmented second cropped image **140**BA. In some implementations, to generate the augmented second cropped image **140**BA, the sample augmenter **200** duplicates (i.e., copies) a first portion **210** of the second cropped image **140**B and overlays the duplicated first portion **210** of the second cropped image **140**B on a second portion **220** of the second cropped image **140**B to form the augmented second cropped image **140**BA (FIG. **2**).

Referring now to FIG. **2**, the sample augmenter **200** may "cut" or copy or duplicate a first portion **210** of the second cropped image **140**B and "paste" the copied first portion **210** over a different second portion **220** of the same second cropped image **140**B, thus generating an augmented second cropped image **140**BA of the original second cropped image **140**B. In some implementations, the copied or duplicated first portion **210** of the second cropped image **140**B has a particular or pre-selected shape. The size and the shape of the duplicated first portion **210** of the second cropped image **140**B may be varied. For example, the duplicated first portion **210** of the second cropped image **140**B has a rectangular shape. The length and width of the rectangular shape may vary based on user configuration and/or parameters of the samples **112** or model **150**. In some implementations, the rectangular shape is similar to a "scar" portion as described in more detail below.

In some examples, to generate the augmented second cropped image **140**BA, the sample augmenter **200** selects the first portion **210** at a first random location of the second cropped image **140**B, duplicates the first portion **210** of the second cropped image **140**B, and overlays or places the duplicated first portion **210** of the second cropped image **140**B on a second portion **220** at a second random location on the second cropped image **140**B. To augment the second cropped image **140**B, the two random locations may be different locations on the second cropped image **140**B. As a result, the augmented second cropped image **140**BA is provided to enhance or improve the training of the machine learning model **150** as compared to being trained on unaugmented training samples **112** alone.

Referring back to FIG. **1**, the model trainer **110**, in some examples, trains a machine learning model **150** using both the first cropped image **140**A and the augmented second cropped image **140**BA. In some implementations, the machine learning model **150** is trained using a cross-entropy loss. For example, the training objective of the machine learning model **150** may be expressed as:

$$E_{x\in X}\{\mathrm{CE}(g(c(x)),0)+\mathrm{CE}(g(\mathrm{CP}(c(x))),1)\} \tag{1}$$

In Equation (1), the c(x) function provides the cropped image (e.g., the first cropped image **140**A or the second cropped image **140**B) at a random location x. Moreover, X denotes a normal data distribution, CP (·) denotes a "cut" and "paste" augmentation as described above, g denotes an output of classifier (e.g., a binary classifier or finer-grained classifier) parameterized by a network, and CE (·,·) denotes the cross-entropy loss. The model trainer **110** may include a loss calculator **160**. As shown in Equation (1), in some implementations, the loss calculator **160** determines a first cross-entropy loss **162**, **162***a* based on a prediction **152** made by the machine learning model **150** when provided the first cropped image **140**A as input. Additionally or alternatively, the model trainer **110** determines a second cross-entropy loss **162**, **162***b* based on a second prediction **152** made by the machine learning model **150** when provided the augmented second cropped image **140**BA as input. The loss calculator **160** may determine an overall cross-entropy loss **162**, **162***c* (e.g., total cross-entropy loss) based on the first cross-entropy loss **162***a* and the second cross-entropy loss **162***b* (e.g., by summing the first cross entropy loss **162***a* and the second cross entropy loss **162***b* as shown in the equation (1)). The loss **162** is provided back to the model **150** to adjust parameters (e.g., weights) of the model **150** train or fine-tune the model **150**.

Referring again to FIG. **2**, in some implementations, the sample augmenter **200** generates the augmented second cropped image **140**BA based on the second cropped image **140**B. In the illustrative example shown in the FIG. **2**, each of the first cropped image **140**A and the second cropped image **140**B includes a mesh pattern. The augmenter **200** "cuts" or copies the first portion **210** of the second cropped image **140**B (i.e., a rectangular portion at the lower right corner of the second cropped image **140**B) and overlays or places the duplicated first portion **210** on the second portion **220** of the second cropped image **140**B (i.e., a rectangular portion on the upper left corner of the second cropped image **140**B) to form or generate the augmented second cropped image **140**BA including a misaligned mesh pattern caused by the "pasted" first portion **210** of the second portion **220** of the second cropped image **140**B.

The location (or position or orientation) of the first portion **210** of the second cropped image **140**B and the second portion **220** of the second cropped image **140**B are not limited to the specific locations (or positions or orientations) discussed herein. For example, the sample augmenter **200** copies or duplicates the first portion **210** at a random location on the second cropped image **140**B (e.g., the center portion) and overlays or places the duplicated first portion **210** over the second portion **220** at a random location on the second cropped image **140**B (e.g., the upper right corner side) to generate the augmented second cropped image **140**BA. In some implementations, the first portion **210** and the second portion **220** are selected at different random locations within the second cropped image **140**B to generate the augmented second cropped image **140**BA that can be used to train the machine learning model **150**. In some implementations, the length and width of the rectangular shape (i.e., first portion and the second portion) may be varied. While in the example of FIG. **2** a size of the first portion **210** and the second portion **220** are the same, in some implementations, the size of the first portion **210** and the second portion **220** are different. As shown in the FIG. **2**, the duplicated first portion **210** included in the augmented second cropped image **140**BA provides the anomalies (i.e., misaligned mesh pattern) to the mesh pattern of the second cropped image **140**BA.

Additionally or alternatively, the model trainer **110** may further enhance the augmented second cropped image **140**BA to further provide valuable training for the machine learning model **150**. In some implementations, the sample augmenter **200** of the model trainer **110** rotates the duplicated first portion **210** of the second cropped image **140**B by a pre-selected degree of rotation (i.e., in a clockwise or counter-clockwise direction) or a random degree of rotation (i.e., in the clockwise or counter-clockwise direction) prior to overlaying the duplicated first portion **210** on the second portion **220** of the second cropped image **140**B. Additionally or alternatively, the augmenter **200** of the model trainer **110** applies a color jitter to the duplicated first portion **210** of the second cropped image **140**B prior to overlaying the duplicated first portion **210** on the second portion **220** of the second cropped image **140**B. For example, the augmenter **200** of the model trainer **110** randomly changes at least one of the brightness, contrast, or saturation of the duplicated first portion **210** of the second cropped image **140**B to apply the color jitter. Applying the color jitter and the rotation are helpful for some images that include a pattern resistant to augmentation from just the duplication and overlaying technique and require further augmentation to provide valuable training.

In some implementations, the sample augmenter **200** of the model trainer **110** may rotate the duplicated portion of the second cropped image **140**B by a pre-selected degree of rotation (in the clockwise or counter-clockwise direction) or a random degree of rotation (in the clockwise or counter-clockwise direction) and then apply the color jitter to the duplicated first portion of the second cropped image **140**B prior to overlaying the duplicated first portion on the second portion of the second cropped image **140**B. In some implementations, the sample augmenter **200** of the model trainer **110** may apply the color jitter to the duplicated first portion of the second cropped image **140**B and then rotate the duplicated portion of the second cropped image **140**B by a pre-selected degree of rotation (in the clockwise or counter-clockwise direction) or a random degree of rotation (in the clockwise or counter-clockwise direction) prior to overlaying the duplicated first portion on the second portion of the second cropped image **140**B.

The duplication and overlaying technique (along with the color jitter and/or the rotation features) introduces a spatial irregularity. For example, by overlaying "rectangular patches" (e.g., the first portion **210** of the second cropper image **140**B) of different size, aspect ratio, and rotation angles on the second portion **220** of the second cropper image **140**B, the augmentation data is more diversified for enhanced training of the machine learning model **150**.

Referring to FIG. **3**, in some implementations, an example system **100**, **100**B includes an image cropper **120**, **120**B for cropping an image of one or more training samples **112** into a plurality of cropped images including the first cropped image **140**A, the second cropped image **140**B, and a third cropped image **140**C. Each of the first cropped image **140**A, the second cropped image **140**B, and the third cropped image **140**C may be different from each other. That is the image cropper **120** crops three different portions of the original image for the first cropped image **140**A, the second cropped image **140**B, and the third cropped image **140**C. The portions of the image in the training samples **112** that the image cropper **120** selects to crop may be pseudo-random or random. The first, second, and third cropped image **140**A, **140**B, **140**C may be the same size or different sizes.

The model trainer **110** may include a sample augmenter **200**, **200**B. The sample augmenter **200**B is configured to generate the augmented second cropped image **140**BA and an augmented third cropped image **140**CA based on the third cropped image **140**C. As discussed above, the image cropper **120**, for each image in the training samples **112**, crops the image of the training samples **112** into the plurality of cropped images which includes, in some examples, the first cropped image **140**A, the second cropped image **140**B, and the third cropped image **140**C. The sample augmenter **200**B may generate other quantities of cropped images **140** as well.

Referring now to FIG. **4**, in some implementations, the sample augmenter **200** receives the third cropped image **140**C for each of the training samples **112** and generates an augmented third cropped image **140**CA. Optionally, to generate the augmented third cropped image **140**CA, the sample augmenter **200**, similar to portions **210**, **220**, duplicates (i.e., copies) a first portion **230** of the third cropped image **140**C and overlays the duplicated first portion **230** of the third cropped image **140**C on a second portion **240** of the third cropped image **140**C to form the augmented third cropped image **140**CA. That is, the sample augmenter **200** may "cut" or copy a portion **230** of the third cropped image **140**C and "paste" the copied portion **230** over a different portion **240** of the same third cropped image **140**C, thus augmenting the original third cropped image **140**C. In particular, the copied or duplicated portion **230** of the third cropped image **140**C has a long thin rectangular shape, which may be referred to as a "scar" portion **230**. In some implementations, the "scar" portion **230** is smaller than the first portion **210** (i.e., the "rectangular patch") included in the augmented second cropped image **140**BA.

In some examples, to generate the augmented third cropped image **140**CA, the sample augmenter **200** selects and duplicates the first portion **230** at a random location on the third cropped image **140**C (i.e., the first portion **230** in the long thin rectangular shape) and overlays or places the duplicated portion **230** of the third cropped image **140**C on the second portion **240** at a random location on the third cropped image **140**C. In some implementations, the first portion **230** and the second portion **240** are located at different locations. As a result, the augmented third cropped image **140**CA with the "scar" portion **230** is provided to enhance or improve the training of the machine learning model **150**.

Additionally or alternatively, the sample augmenter **200** of the model trainer **110** may further enhance the augmented third cropped image **140**CA in the same or similar manner as the second cropped image **140**BA to provide further valuable training to the machine learning model **150**. In some implementations, the sample augmenter **200** of the model trainer **110** rotates the duplicated first portion **230** of the third cropped image **140**C (e.g., "scar" portion) by a pre-selected degree of rotation (in the clockwise or counter-clockwise direction) or a random degree of rotation (in the clockwise or counter-clockwise direction) prior to overlaying the duplicated first portion **230** on the second portion **240** of the third cropped image **140**C. In some implementations, the model trainer **110** may apply the color jitter to the duplicated first portion **230** of the third cropped image **140**C (e.g., "scar" portion) prior to overlaying the duplicated first portion **230** on the second portion **240** of the third cropped image **140**C.

For example, the sample augmenter **200** of the model trainer **110** randomly changes at least one of the brightness, contrast, or saturation of the duplicated first portion **230** of the third cropped image **140**C to apply the color jitter. In some implementations, the augmenter **200** of the model trainer **110** may rotate the duplicated first portion **230** of the third cropped image **140**C (e.g., "scar" portion) by a pre-selected degree of rotation (in the clockwise or counter-clockwise direction) or a random degree of rotation (in the clockwise or counter-clockwise direction) and apply the color jitter to the duplicated first portion **230** of the third cropped image **140**C prior to overlaying the duplicated first portion **230** on the second portion **240** of the third cropped image **140**C. Applying the color jitter and the rotation are helpful for some images that include a pattern resistant to augmentation from just the duplication and overlaying technique and require further augmentation to provide valuable training. The duplication and overlaying technique (along with the color jitter and/or rotation features) introduces a spatial irregularity. For example, by overlaying the long thin rectangular "scar" (i.e., the first portion of the third cropped image **140**C) of different size, aspect ratio, and rotation angles on the random second portion of the third cropped image **140**C, diverse augmentation data is generated by the sample augmenter **200**.

With continued reference to FIG. **4**, in some implementations, the sample augmenter **200** generates the augmented second cropped image **140**BA and the augmented third cropped image **140**CA based on the second cropped image **140**B and third cropped image **140**C, respectively. As discussed above, the first cropped image **140**A and the augmented second cropped image **140**BA are generated to provide additional training images to the machine learning model **150** (FIGS. **2** and **4**). As illustrated in schematic view **400**, in addition to the first cropped image **140**A and the augmented second cropped image **140**BA, the augmented third cropped image **140**CA provides yet additional training images to the machine learning model **150**.

Here, each of the first cropped image **140**A, the second cropped image **140**B, and the third cropped image **140**C includes a mesh pattern. As shown in the FIG. **4**, the augmenter **200** "cuts" or copies the first portion **230** of the third cropped image **140**C (e.g., a long thin rectangular portion having an approximate 1:6 width-to-length ratio at the lower right corner of the third cropped image **140**C) and overlays or places the duplicated first portion **230** on the second portion **240** of the third cropped image **140**C (i.e., a long thin rectangular portion having an approximate 1:6 width-to-length ratio on the upper left corner of the third cropped image **140**C) to form or generate the augmented third cropped image **140**CA including a misaligned mesh pattern caused by the "pasted" first portion **230** of the third cropped image **140**C. The location (or position) of the first portion **230** of the third cropped image **140**C and the second portion **240** of the third cropped image **140**C are not limited to the specific locations (or positions) called out above.

For example, the sample augmenter **200** copies or duplicates a first portion **230** at a random location on the third cropped image **140**C (e.g., the center portion) and overlays or places the duplicated first portion **230** on a second portion **240** at a random location on the third cropped image **140**C (e.g., the upper right corner side) to generate the augmented third cropped image **140**CA. In some implementations, the random locations are different locations within the third cropped image **140**C to generate the augmented third cropped image **140**CA that can be used to train the machine learning model **150**. In some implementations, the width-to-length ratio of the long thin rectangular shape (e.g., approximate 1:6 or a greater) may be varied. In this example, the duplicated first portion **203** included in the augmented third cropped image **140**CA provides the "scar" like anomalies (i.e., a "scar" mesh pattern) to the mesh pattern of the third cropped image **140**CA. In some implementations, the "scar" portion is smaller than the first portion **210** included in the augmented second cropped image **140**BA.

FIG. **5** is a flowchart of an example arrangement of operations for a method **500** for training a model **150** for anomaly detection and localization. The method **500**, at operation **502**, includes obtaining, at data processing hardware **12**, a set of training samples **112**. As discussed above, the machine learning model **150** (e.g., convolutional neural network (CNN)) is trained on the set of training samples **112**. Each of the training samples **112** may include an image of normal patterns (i.e., patterns that do not include anomalies). For example, the image of normal patterns is 256×256 image.

At operation **504**, the method **500** includes, during each of one or more training iterations, cropping, by the data processing hardware **12**, the training sample (image) in the training samples **112** to generate a first cropped image **140**A. The method **500**, at operation **506**, includes cropping, by the data processing hardware **12**, the training sample (image) in the training samples **112** to generate a second cropped image **140**B that is different than the first cropped image **140**A. As discussed above, each image from the training samples **112** is cropped into a smaller size image. In some implementations, each 256×256 image in the training samples **112** is cropped into 64×64 image or 32×32 image. The first cropped image **140**A may be different than the second cropped image **140**B. That is, the image cropper **120** crops two different portions for the first cropped image **140**A and the second cropped image **140**B. The portions of the training sample (image) in the training samples **112** that are selected to crop may be pseudo-random or random. The first and second cropped image **140**A, **140**B may be the same size or different sizes.

At operation **508**, the method **500** includes duplicating, by the data processing hardware **12**, a first portion **210** of the second cropped image **140**B and, at operation **510**, overlaying, by the data processing hardware **12**, the duplicated first portion **210** of the second cropped image **140**B on a second portion **220** of the second cropped image **140**B to form an augmented second cropped image **140**BA. The first portion **210** is different than the second portion **220**. As discussed above, in some implementations, the copied or duplicated first portion of the second cropped image **140**B has a particular or pre-selected shape. The size and the shape of the duplicated first portion of the second cropped image **140**B can be varied. For example, the duplicated first portion of the second cropped image **140**B has a rectangular shape. The length and width of the rectangular shape may be varied in accordance with some implementations. In some implementations, to generate the augmented second cropped image **140**BA, the location of the first portion **210** of the second cropped image **140**B and the location of the second portion **220** of the second cropped image **140**B are determined randomly. In some implementations, the method **500** further includes at least one of rotating, by the data processing hardware **12**, the duplicated first portion **210** of the second cropped image **140**B or applying, by the data processing hardware **12**, the color jitter to the duplicated first portion **210** of the second cropped image **140**B.

At operation **512**, the method **500** includes training, by the data processing hardware **12**, the machine learning model **150** with the first cropped image **140**A and the augmented second cropped image **140**BA.

FIG. **6** is a flowchart of an example arrangement of operations for a method **600** for training a model **150** for anomaly detection and localization. The method **600** includes several operations including operations **602**-**610** that align with operations **502**-**510** (FIG. **5**) have been described above in detail with reference to FIG. **5**, and thus, their detailed descriptions are not repeated here. Starting with operation **612**, the method **600** includes cropping, by the data processing hardware **12**, the training sample (image) in the training samples **112** to generate a third cropped image **140**C that is different than the first cropped image **140**A and the second cropped image **140**B. As discussed above, each image from the training samples **112** is cropped into a smaller size image. In some implementations, each 256×256 image in the training samples **112** is cropped into 64×64 image or 32×32 image, although the any resolution image may be cropped into any smaller resolution image portion. The first cropped image **140**A, the second cropped image **140**B, and the third cropped image **140**C may be different from each other. That is, the image cropper **120** crops three different portions for the first cropped image **140**A, the second cropped image **140**B, and the third cropped image **140**C. The portions of the training sample (image) in the training samples **112** that are selected to crop may be pseudo-random or random. The first, second, third cropped image **140**A, **140**B, **140**C may be the same size or different sizes.

At operation **614**, the method **600** includes duplicating, by the data processing hardware **12**, a first portion **230** of the third cropped image **140**C and, at operation **616**, overlaying, by the data processing hardware **12**, the duplicated first portion **230** of the third cropped image **140**C on a second portion **240** of the third cropped image **140**C to form an augmented third cropped image **140**CA. The first portion **230** is different than the second portion **240**. As discussed above, in some implementations, the copied or duplicated first portion **230** of the third cropped image **140**C has a long thin rectangular shape. In some implementations, the first portion **230** and the second portion **240** are selected at different random locations within the third cropped image **140**C to generate the augmented third cropped image **140**CA that can be used to further train the machine learning model **150**. In some implementations, the width-to-length ratio of the long thin rectangular shape (e.g., approximate 1:6 or a greater) may be varied. For example, as shown in the FIG. **4**, the duplicated first portion **230** included in the augmented third cropped image **140**CA provides the “scar” like anomalies (i.e., “scar” mesh pattern) to the mesh pattern of the third cropped image **140**CA. In some implementations, the “scar” portion is smaller than the first portion included in the augmented second cropped image **140**BA. In some implementations, the method **600** further includes at least one of rotating, by the data processing hardware **12**, the duplicated portion of the third cropped image **140**C or applying, by the data processing hardware **12**, the color jitter to the duplicated portion of the third cropped image **140**C.

At operation **618**, the method **600** includes training, by the data processing hardware **12**, the machine learning model **150** with the first cropped image **140**A, the augmented second cropped image **140**BA, and the augmented third cropped image **140**CA.

FIG. **7** is schematic view of an example computing device **700** that may be used to implement the systems and methods described in this document. The computing device **700** is intended to represent various forms of digital computers, such as laptops, desktops, workstations, personal digital assistants, servers, blade servers, mainframes, and other appropriate computers. The components shown here, their connections and relationships, and their functions, are meant to be exemplary only, and are not meant to limit implementations of the inventions described and/or claimed in this document.

The computing device **700** includes a processor **710**, memory **720**, a storage device **730**, a high-speed interface/controller **740** connecting to the memory **720** and high-speed expansion ports **750**, and a low speed interface/controller **760** connecting to a low speed bus **770** and a storage device **730**. Each of the components **710**, **720**, **730**, **740**, **750**, and **760**, are interconnected using various busses, and may be mounted on a common motherboard or in other manners as appropriate. The processor **710** can process instructions for execution within the computing device **700**, including instructions stored in the memory **720** or on the storage device **730** to display graphical information for a graphical user interface (GUI) on an external input/output device, such as display **780** coupled to high speed interface **740**. In other implementations, multiple processors and/or multiple buses may be used, as appropriate, along with multiple memories and types of memory. Also, multiple computing devices **700** may be connected, with each device providing portions of the necessary operations (e.g., as a server bank, a group of blade servers, or a multi-processor system).

The memory **720** stores information non-transitorily within the computing device **700**. The memory **720** may be a computer-readable medium, a volatile memory unit(s), or non-volatile memory unit(s). The non-transitory memory **720** may be physical devices used to store programs (e.g., sequences of instructions) or data (e.g., program state information) on a temporary or permanent basis for use by the computing device **700**. Examples of non-volatile memory include, but are not limited to, flash memory and read-only memory (ROM)/programmable read-only memory (PROM)/erasable programmable read-only memory (EPROM)/electronically erasable programmable read-only memory (EEPROM) (e.g., typically used for firmware, such as boot programs). Examples of volatile memory include, but are not limited to, random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), phase change memory (PCM) as well as disks or tapes.

The storage device **730** is capable of providing mass storage for the computing device **700**. In some implementations, the storage device **730** is a computer-readable medium. In various different implementations, the storage device **730** may be a floppy disk device, a hard disk device, an optical disk device, or a tape device, a flash memory or other similar solid state memory device, or an array of devices, including devices in a storage area network or other configurations. In additional implementations, a computer program product is tangibly embodied in an information carrier. The computer program product contains instructions that, when executed, perform one or more methods, such as those described above. The information carrier is a computer- or machine-readable medium, such as the memory **720**, the storage device **730**, or memory on processor **710**.

The high speed controller **740** manages bandwidth-intensive operations for the computing device **700**, while the low speed controller **760** manages lower bandwidth-intensive operations. Such allocation of duties is exemplary only. In some implementations, the high-speed controller **740** is coupled to the memory **720**, the display **780** (e.g., through a graphics processor or accelerator), and to the high-speed expansion ports **750**, which may accept various expansion cards (not shown). In some implementations, the low-speed controller **760** is coupled to the storage device **730** and a low-speed expansion port **790**. The low-speed expansion port **790**, which may include various communication ports (e.g., USB, Bluetooth, Ethernet, wireless Ethernet), may be coupled to one or more input/output devices, such as a keyboard, a pointing device, a scanner, or a networking device such as a switch or router, e.g., through a network adapter.

The computing device **700** may be implemented in a number of different forms, as shown in the figure. For example, it may be implemented as a standard server **700***a* or multiple times in a group of such servers **700***a*, as a laptop computer **700***b*, or as part of a rack server system **700***c*.

Various implementations of the systems and techniques described herein can be realized in digital electronic and/or optical circuitry, integrated circuitry, specially designed ASICs (application specific integrated circuits), computer hardware, firmware, software, and/or combinations thereof. These various implementations can include implementation in one or more computer programs that are executable and/or interpretable on a programmable system including at least one programmable processor, which may be special or general purpose, coupled to receive data and instructions from, and to transmit data and instructions to, a storage system, at least one input device, and at least one output device.

A software application (i.e., a software resource) may refer to computer software that causes a computing device to perform a task. In some examples, a software application may be referred to as an "application," an "app," or a "program." Example applications include, but are not limited to, system diagnostic applications, system management applications, system maintenance applications, word processing applications, spreadsheet applications, messaging applications, media streaming applications, social networking applications, and gaming applications.

These computer programs (also known as programs, software, software applications or code) include machine instructions for a programmable processor, and can be implemented in a high-level procedural and/or object-oriented programming language, and/or in assembly/machine language. As used herein, the terms "machine-readable medium" and "computer-readable medium" refer to any computer program product, non-transitory computer readable medium, apparatus and/or device (e.g., magnetic discs, optical disks, memory, Programmable Logic Devices (PLDs)) used to provide machine instructions and/or data to a programmable processor, including a machine-readable medium that receives machine instructions as a machine-readable signal. The term "machine-readable signal" refers to any signal used to provide machine instructions and/or data to a programmable processor.

The processes and logic flows described in this specification can be performed by one or more programmable processors, also referred to as data processing hardware, executing one or more computer programs to perform functions by operating on input data and generating output. The processes and logic flows can also be performed by special purpose logic circuitry, e.g., an FPGA (field programmable gate array) or an ASIC (application specific integrated circuit). Processors suitable for the execution of a computer program include, by way of example, both general and special purpose microprocessors, and any one or more processors of any kind of digital computer. Generally, a processor will receive instructions and data from a read only memory or a random access memory or both. The essential elements of a computer are a processor for performing instructions and one or more memory devices for storing instructions and data. Generally, a computer will also include, or be operatively coupled to receive data from or transfer data to, or both, one or more mass storage devices for storing data, e.g., magnetic, magneto optical disks, or optical disks. However, a computer need not have such devices. Computer readable media suitable for storing computer program instructions and data include all forms of non-volatile memory, media and memory devices, including by way of example semiconductor memory devices, e.g., EPROM, EEPROM, and flash memory devices; magnetic disks, e.g., internal hard disks or removable disks; magneto optical disks; and CD ROM and DVD-ROM disks. The processor and the memory can be supplemented by, or incorporated in, special purpose logic circuitry.

To provide for interaction with a user, one or more aspects of the disclosure can be implemented on a computer having a display device, e.g., a CRT (cathode ray tube), LCD (liquid crystal display) monitor, or touch screen for displaying information to the user and optionally a keyboard and a pointing device, e.g., a mouse or a trackball, by which the user can provide input to the computer. Other kinds of devices can be used to provide interaction with a user as well; for example, feedback provided to the user can be any form of sensory feedback, e.g., visual feedback, auditory feedback, or tactile feedback; and input from the user can be received in any form, including acoustic, speech, or tactile input. In addition, a computer can interact with a user by sending documents to and receiving documents from a device that is used by the user; for example, by sending web pages to a web browser on a user's client device in response to requests received from the web browser.

A number of implementations have been described. Nevertheless, it will be understood that various modifications may be made without departing from the spirit and scope of the disclosure. Accordingly, other implementations are within the scope of the following claims.

What is claimed is:

1. A method for training a machine learning model, the method comprising:

obtaining, at data processing hardware, a set of training samples; and

during each of one or more training iterations, for each training sample in the set of training samples:

cropping, by the data processing hardware, the training sample to generate a first cropped image;

cropping, by the data processing hardware, the training sample to generate a second cropped image that is different than the first cropped image;

duplicating, by the data processing hardware, a first portion of the second cropped image;

overlaying, by the data processing hardware, the duplicated first portion of the second cropped image on a second portion of the second cropped image to form an augmented second cropped image, the first portion different than the second portion; and

training, by the data processing hardware, the machine learning model with the first cropped image and the augmented second cropped image.

2. The method of claim **1**, wherein the duplicated first portion of the second cropped image has a rectangular shape with a variable length and width.

3. The method of claim **1**, wherein overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image comprises:

selecting a random location of the second cropped image for the second portion of the second cropped image; and

overlaying the duplicated first portion of the second cropped image at the selected random location.

4. The method of claim **1**, wherein training the machine learning model with the first cropped image and the augmented second cropped image comprises:

determining a first cross-entropy loss for the first cropped image;

determining a second cross-entropy loss for the augmented second cropped image; and

determining a total cross-entropy loss based on the first cross-entropy loss and the second cross-entropy loss.

5. The method of claim **4**, wherein the total cross-entropy loss comprises a sum of the first cross-entropy loss and the second cross-entropy loss.

6. The method of claim **1**, wherein each training sample is unlabeled.

7. The method of claim **1**, wherein the machine learning model comprises a convolutional neural network.

8. The method of claim **1**, wherein the machine learning model is configured to detect anomalous patterns in image data.

9. The method of claim **1**, further comprising, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, rotating, by the data processing hardware, the duplicated first portion of the second cropped image.

10. The method of claim **1**, further comprising, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, applying, by the data processing hardware, a color jitter to the duplicated first portion of the second cropped image.

11. A system comprising:

data processing hardware; and

memory hardware in communication with the data processing hardware, the memory hardware storing instructions that when executed on the data processing hardware cause the data processing hardware to perform operations comprising:

obtaining a set of training samples; and

during each of one or more training iterations, for each training sample in the set of training samples:

cropping the training sample to generate a first cropped image;

cropping the training sample to generate a second cropped image that is different than the first cropped image;

duplicating a first portion of the second cropped image;

overlaying the duplicated first portion of the second cropped image on a second portion of the second cropped image to form an augmented second cropped image, the first portion different than the second portion; and

training a machine learning model with the first cropped image and the augmented second cropped image.

12. The system of claim **11**, wherein the duplicated first portion of the second cropped image has a rectangular shape with a variable length and width.

13. The system of claim **11**, wherein overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image comprises:

selecting a random location of the second cropped image for the second portion of the second cropped image; and

overlaying the duplicated first portion of the second cropped image at the selected random location.

14. The system of claim **11**, wherein training the machine learning model with the first cropped image and the augmented second cropped image comprises:

determining a first cross-entropy loss for the first cropped image;

determining a second cross-entropy loss for the augmented second cropped image; and

determining a total cross-entropy loss based on the first cross-entropy loss and the second cross-entropy loss.

15. The system of claim **14**, wherein the total cross-entropy loss comprises a sum of the first cross-entropy loss and the second cross-entropy loss.

16. The system of claim **11**, wherein each training sample is unlabeled.

17. The system of claim **11**, wherein the machine learning model comprises a convolutional neural network.

18. The system of claim **11**, wherein the machine learning model is configured to detect anomalous patterns in image data.

19. The system of claim **11**, wherein the operations further comprise, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, rotating the duplicated first portion of the second cropped image.

20. The system of claim **11**, wherein the operations further comprise, prior to overlaying the duplicated first portion of the second cropped image on the second portion of the second cropped image, applying a color jitter to the duplicated first portion of the second cropped image.

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